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EEG Pathology Detection Based on Deep Learning

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ABSTRACT With the advancement of machine learning technologies, particularly deep learning, the automated systems to assist human life are flourishing. In this paper, we propose an automatic electroencephalogram (EEG) pathology detection system based on deep learning. Various types of pathologies can affect brain signals. Thus, the brain signals captured in the form of EEG signals can indicate whether a person suffers from pathology or not. In the proposed system, the raw EEG signals are processed in the form of a spatio-temporal representation. The spatio-temporal form of the EEG signals is the input to a convolutional neural network (CNN). Two different CNN models, namely, a shallow model and a deep model, are investigated using transfer learning. A fusion strategy based on a multilayer perceptron is also investigated. The experimental results on the Temple University Hospital EEG Abnormal Corpus v2.0.0 show that the proposed system with the deep CNN model and fusion achieves 87.96% accuracy, which is better than some reported accuracy rates on the same corpus.

INDEX TERMS EEG pathology, deep learning, EEG processing, Temple University Hospital EEG Abnormal Corpus.

I. INTRODUCTION

The advancement of machine learning (ML) and artificial intelligence technologies has enabled the development of sophisticated systems that are useful to everyday life. Internet of Things (IoT) and cloud computing technology brought a revolution in distributed computing and storage. A smart healthcare system utilizes the IoT, cloud computing, next-generation communication protocol, and advanced ML technologies to offer health services to clients. Accuracy and real-time processing are two central ideas of the smart healthcare system. For patients in a critical condition and those who need immediate diagnosis and treatment, the diagnosis must be accurate and in real time; otherwise, serious complications may arise and the patient's life may be endangered. In this case, the acquired signals from the patients should be transmitted fast to the processing unit, and the processing should be accurate. Feedback from the processing unit should arrive at the stakeholders in real time. Fortunately, IoT, edge and cloud computing, and recent ML techniques enable us to achieve accuracy and real-time requirement to a certain extent.

The healthcare sector is experiencing rapid growth due to its important services and the enormous revenues it is generating. Serious competition is occurring among healthcare service providers to offer accurate, fast, reliable, and low-cost services [1]. The sector has been revolutionized by technologies such as IoT, cloud, and deep learning, which have recently been the focus of research. IoT–cloud integration has led to the development of low-cost, sophisticated, and intelligent healthcare sensors in the form of smart wearable devices. These sensors are available for a plethora of medical applications such as measuring blood glucose, blood pressure, temperature, electrocardiogram (ECG), electroencephalogram (EEG), stress, and body weight.

Complex, real-time, and big data such as EEG usually require advanced processing and large storage facilities. Thus, we use technologies such as big data processing, cloud computing, and deep learning. Processing and analyzing big data is even more difficult in a smart city because thousands of interconnected IoT devices and sensors may exist, thereby producing such data continuously [2]. We need a smart healthcare framework that not only solves these issues

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related to data processing but also satisfies the requirements of all the smart city stakeholders and provides reliable and low-cost healthcare services.

In a smart city scenario offering smart healthcare services, real-time decision-making capability is necessary in response to the emergency needs of patients. Healthcare services should always be available at the disposal of all smart city residents and medical practitioners. Mobile ambulances and other facilities should also be made available as fast as possible at the time of emergency. Thus, to manage such complex decision making, we need cognitive intelligence imparted to the system to make it think and act as humans do. Many recent studies have started to use cognitive technology for smart city frameworks [3].

A smart healthcare system works by utilizing a variety of smart sensors or IoT devices, which are either fixed to or worn by the patient or may be placed in the surrounding environment such as smart homes or smart offices [4]. These IoT devices or smart sensors continuously monitor patients and generate real-time medical data by observing and recording patient responses such as body movements, facial expressions and emotions, EEG, heartbeat, blood pressure, blood glucose, temperature, and voice. Then, the medical data are processed to determine the health status of the patient. The healthcare system also needs to determine whether the patient requires emergency care. Other stakeholders have to be aware of the patient's health status so that they can analyze and monitor his/her health. All of these requirements and issues make cognitive intelligence important for such a smart healthcare paradigm. The research community has exerted considerable effort in this area recently [5]. Some of the developments are discussed in this paper.

A study proposed a smart healthcare system [6] using IoT and cloud technology and also discussed challenges and issues faced in the area as well as the monitoring of environmental characteristics such as temperature and humidity. Another research study [7] used facial images and voice signals to access electronic health records to monitor patients. Researchers [8] integrated IoT–cloud technologies to develop a healthcare system for emotion detection. In another study [9], IoT and cloud technology were integrated into a real-time system for smart healthcare. Another study [10] used edge and cognitive computing for a similar application. Therefore, various technological integrations have been conducted recently to achieve smart healthcare objectives.

EEG signal sensing and monitoring has been performed to detect brain diseases and disorders such as stroke, Alzheimer's disease, and epilepsy. EEG is a low-cost and non-intrusive method to monitor brain activity. Recording, processing, and analyzing EEG signals are time-consuming activities. Medical experts and good knowledge are required to analyze EEG data. Automated systems developed for real-time EEG processing require extensive training before they can be used in clinical systems. Techniques, such as deep learning, are now being utilized to understand EEG data. Also, an increase in brain-related disorders has been observed, which has led researchers to develop EEG diagnosis systems for smart healthcare applications. Many recent studies have focused on this area such as the treatment of stroke, Alzheimer's disease, depression, and hemorrhage [11]–[15]. Such medical disorders need real-time patient monitoring and emergency services. If the services are delayed, the result may be catastrophic and life threatening for patients. Moreover, smart healthcare systems that diagnose these ailments should be intelligent, reliable, and accurate. Medical representatives should have access to healthcare records and be able to provide expert services when needed. In case of emergency, smart ambulances and smart health centers should be readily available.

To meet the aforementioned challenges, we propose a smart healthcare system for pathology diagnosis based on EEG signals. Our system analyzes and processes EEG pathology data and classifies them as either normal or abnormal. Abnormal EEG can come from any of the brain-related disorders. Our system uses multimodal IoT smart sensors to capture real-time EEG data and sends it to the cloud server for processing. The acquired signals are EEG, movement, emotions, and voice, which are pre-processed to determine the patient's health status. The data are then transferred to the deep learning module, which classifies the EEG pathology data as either normal or abnormal. Finally, all the processed data and results are transmitted to the server, which subsequently notifies the concerned medical practitioners if emergency services are required. The medical experts analyze the electronic healthcare records to monitor the patient's condition.

The proposed EEG pathology detection system involves a convolutional neural network (CNN). Two different CNN models are investigated: shallow and deep. The deep CNN model is used in transfer learning. Parallel deep CNN models across time are fused using a multilayer perceptron (MLP). The contribution of this study is as follows: (i) use of the CNN model to detect EEG pathology, (ii) comparison between shallow and deep CNN models in terms of EEG pathology detection, and (iii) fusion of deep CNN models using MLP to increase detection accuracy.

The rest of the paper is organized as follows. Section II presents related studies. Section III describes the proposed system. Section IV provides the experimental results and discussion. Section V draws conclusions.

II. RELATED STUDY

In this section, we discuss some of the studies and frameworks related to EEG-based pathology detection, and cognitive and smart healthcare.

A. EEG SIGNALS AND COGNITIVE TECHNOLOGY

EEG signals represent electrical waves of the brain captured by sensors called electrodes. Different areas of the brain are responsible for different tasks. For example, the movement of arms, fingers, and legs are controlled by the motor cortex area of the brain. Broca's area controls the muscles of the mouth. EEG signals are made up of many frequency components. Researchers roughly divided the frequency regions into several frequency bands called delta (1–3 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (12–30 Hz), and gamma (30–100 Hz). Each band has specific characteristics. The beta and gamma bands are active in motor activities [16], and the alpha band is more active than other bands in memory recall [17]. Thus, EEG signals can be used in cognitive computing.

Cognitive technology has recently found extensive use in the smart city paradigm and has transformed the entire approach of smart healthcare by imparting intelligence and human-like behavior. Advanced smart sensors, IoT, and cloud computing have improved the smart healthcare services in terms of innovativeness, mobility, cost, speed, and accuracy. Some of the smart healthcare services that use cognitive technology include mobile healthcare services, automatic disease diagnosis and emergency response, robot-controlled smart medical devices and equipment, remote patient monitoring and tracking, intelligent medicine dispensing, and smart electronic healthcare records. Cognitive healthcare systems operate by communicating with interconnected IoT smart healthcare sensors attached to the patient's body. These systems are capable of processing multimodal data in real time to monitor the patients and provide emergency response. Cognitive systems also collaborate with the latest technologies, such as 5G, to improve communication standards [3]. These systems also use technologies, such as Kinect, in patient activity recognition. Cognitive healthcare systems use IoT, smart sensors, and cloud computing to extract and process complex information from multi-modal data. These systems do not require human assistance and can make human-like intelligent decisions.

Researchers have started to use cognitive-based systems for different smart frameworks in various areas. A framework that used cognitive technology was proposed in [18] for smart city modeling and sustainability enhancement. In [19], researchers imparted human behavior cognitive ability to their smart framework using cognitive technology. A system in [20] proposed the modeling of relative human knowledge using cognitive systems for smart city application. A system for natural language processing was developed in [21] to answer questions in a human-like manner. Big data analytics were also performed in [22] using cognitive technology. Some healthcare applications that use physiological and psychological [23] data also use cognitive systems to impart intelligence. Some researchers applied cognitive intelligence to emotion-aware systems [4], while others used it in emotion recognition [8] and voice and facial expression detection [24].

B. SMART HEALTHCARE

Smart healthcare frameworks have provided social and economic advancements and are thus being used extensively in smart cities. Numerous recent works have proposed smart healthcare systems and services, based on the IoT–cloud technology. A system to find the best route to the nearest health center was developed in [1] by using smart devices and sensors. In [25], a smart healthcare framework used electronic healthcare records to enhance services. Another smart healthcare system [18] included real-time monitoring of glucose level for diabetics; this system also used cognitive behavior to impart intelligence to the system. In [26], the researchers proposed a smart ambulance with cognitive intelligence capability; this ambulance used robots for driving and was built to provide emergency services to cardiac patients. Some smart healthcare frameworks were built to detect forgery of medical and healthcare-related images [27].

In this study, we propose a cognitive smart healthcare system for pathology detection based on EEG. We impart cognitive intelligence with IoT–cloud integration to the smart healthcare system. Our cognitive approach solves key problems related to the smart healthcare domain.

C. EEG PATHOLOGY CLASSIFICATION

Deep learning techniques have aided the recent technological advancements in automated EEG-related disease diagnosis and detection systems. Automated medical diagnosis is now the most researched area and is being used for various diseases, disorders, and medical conditions such as brain hemorrhage, depression, stroke, Alzheimer's disease, and epileptic seizures [11]–[15]. Apart from using deep learning, these automated diagnostic systems also use ML-based techniques such as principal component analysis, regression, support vector machines, and random forest. However, deep learning models with automated feature extraction ability have enhanced EEG decoding performance. Furthermore, EEG pathology diagnosis also aims to detect abnormal medical conditions among patients by analyzing their EEG. Such systems could assist patients who need emergency care as in cases related to seizures and strokes.

Some EEG pathology datasets are available online but most of them are small in size and inappropriate for deep learning-based models. Temple University Hospital (TUH) [28] dataset is the only public EEG pathology dataset that has been recently added online. This dataset consists of approximately 3,000 abnormal EEG data. As this dataset is recent, it has not been used by many researchers. We found three works related to EEG pathology detection based on the TUH dataset. TUH researchers [29] proposed multi-layer CNN architecture and achieved approximately 79% accuracy in pathology detection. Another study [30] used multiple CNN architecture and improved the pathology detection accuracy to 86%. The third study [31] applied popular CNN-based models, such as VGGNet and AlexNet, to achieve 86.59% and 87.32% accuracy, respectively. Since EEG has a highly dynamic nature, ML models have not achieved much success in EEG decoding. EEG characteristics also vary for different persons and medical conditions. Thus, building an automated EEG diagnosis system for clinical purposes is a difficult task.

Deep learning techniques such as CNN have been utilized for epilepsy diagnosis. In [32], researchers proposed the

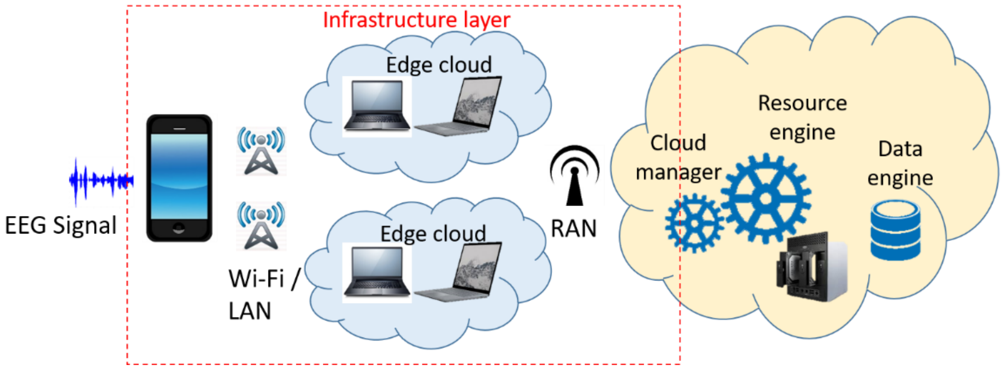

FIGURE 1. Illustration of the cloud-based EEG pathology detection framework.

CNN model for seizure detection and visualization. Another work [33] proposed seizure detection using EEG recording with a large number of channels. Some studies, such as [14], used CNN in combination with autoencoders and achieved better performance than using only CNN.

III. MATERIAL AND METHOD

A. FRAMEWORK

A cloud-based framework for EEG pathology detection is developed. In the framework, there are mainly three ingredients. Figure 1 shows an illustration of the overall framework. The EEG signals are captured by a headset of electrodes. The headset acts as an IoT device. Alternatively, different IoT devices can be designed to capture EEG signals of different parts of the brain. The EEG signals are transmitted to a mobile edge computing (MEC) server via a short-range communication protocol such as Wi-Fi or local area network (LAN). The MEC distributes the signals to different edge processors which preprocess the signal. The preprocessing includes removing noise artifacts and converting the signals into frequency-domain signals. The edge processors are low cost and low processing units that can also act as IoTs. They are used to reduce the burden of transmitting huge amount of data to the cloud. Some edge caches can also be used to store the trained parameters of the model to make a decision faster. The 2D signals are transmitted to a main cloud via a radio access network (RAN). The main cloud has several components such as a cloud manager, a resource engine, and a data storage. The cloud manager authenticates the users and the stakeholders, and distributes the work to the resource engine. With the help of the data storage, the resource engine does the main processing and classification of the EEG signals. The decision on the signals (pathology or non-pathology) is then transferred to the users and the stakeholders via the cloud manager. Depending on the decision, necessary action is taken by the stakeholders to provide an utmost care to the users.

B. DATABASE

The TUH EEG Abnormal Corpus v2.0.0 was used in the experiments in this study [28]. A total of 2,383 participants were included, among whom 1,385 had normal EEG recordings and 998 had abnormal EEG recordings in the database. The database was divided into train and evaluation subsets. In the train subset, 1,237 were in the normal class and 893 were in the abnormal class. In the evaluation subset, the respective numbers were 148 and 105. Some subjects appear more than once in the train subset. The train and evaluation subsets did not show any overlapping of subjects. The EEG signals of some subjects were recorded in multiple sessions. In the database, 512.01 and 526.05 hours of data were observed in the train subset in the normal and abnormal classes, respectively. The numbers were 55.46 and 47.48 hours, respectively, in the evaluation subset. The subjects were evenly distributed between male and female. Table 1 shows gender-based distribution of the files in the database. The average age was 51.6 years old with standard deviation of 55.9.

TABLE 1. Number of samples in the TUH EEG Abnormal Corpus v2.0.0. (M = Male, F = Female).

	Normal		Abnormal		Total	
	M	F	M	F	M	F
Evaluation	65	85	63	63	128	148
Train	603	768	667	679	1270	1447
Total	668	853	730	742	1398	1595

The EEG recordings varied in the number of channels (electrodes). The most common was 31 channels per recording, and the minimum number of channels was 21. We removed the recordings that had more than 21 channels. In the recordings, the first minute was deleted from each file because of noise artifact. Then, 87% of the recordings were sampled at 250 Hz, 8.3% at 256 Hz, 3.8% at 400 Hz, and 1% at 512 Hz. In the experiments, the recordings were downsampled at 100 Hz. Each EEG recording length was approximately 20 minutes. Human rates verified the recordings; 99% agreement was observed between the rates in the train subset and 100% in the evaluation subset.

C. PROPOSED EEG PATHOLOGY DETECTION SYSTEM

The proposed EEG pathology detection system includes a preprocessing step and a CNN-based feature extraction and classification step. This section describes the steps in details.

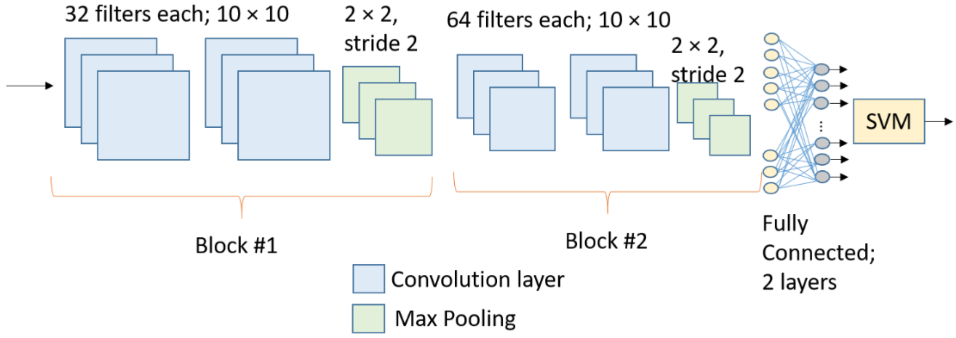

FIGURE 2. Structure of the shallow CNN model.

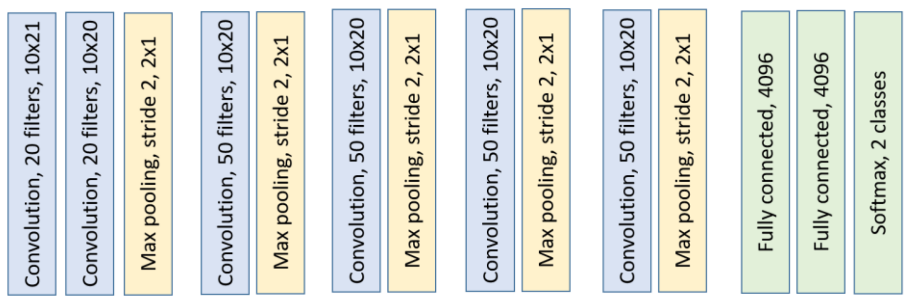

FIGURE 3. Architecture of AlexNet.

The preprocessing of the raw EEG signals contains two stages as follows.

Stage 1: The EEG signal from each electrode is converted into a frequency-domain signal using the Fourier transform. Three band-pass filters are applied to the frequency-domain signal. The frequency bands are (1 – 7 Hz), (8 – 30 Hz), and (31 – 100 Hz). Therefore, we have three band-limited signals from each EEG signal.

Stage 2: The band-limited signals are arranged for all the electrodes row-wise. For each band-limited signal, we have 21 rows corresponding to 21 electrodes' EEG. For one minute of EEG signal, we have a 21×6000 dimensional matrix for each band, where 6000 represents the number of samples per minute (60 seconds $\times$ 100 samples per second).

Once the preprocessing is done, the matrices are fed to a CNN model. Two different CNN models are investigated in the study. The first one is a shallow CNN model, which is designed by us. The second one is the AlexNet [34], and we use it as a pretrained model.

In the shallow CNN model, input matrices have size 227×227, and there are three matrices. The three matrices correspond to three bands mentioned earlier. The matrices obtained from the preprocessing step are resampled to the input matrix size. There are two blocks in the block; each block has two convolutional layers followed by a Rectifier linear unit and a max pooling. Figure 2 shows the structure of the shallow CNN model. After the second block, the features are flattened. Then we have two fully connected layers. All the weights are initialized randomly using a Gaussian distribution having the mean equals to zero and the standard deviation equals to 0.01. A mini-batch stochastic gradient decent algorithm is used to optimize the weights. The batch size is set to 50. There is a 50% dropout in the fully-connected layers. After the final fully-connected layer, the features are fed to a support vector machine (SVM) classifier [35]. A grid search method is applied to find the optimal parameters of the SVM. In the experiments, linear kernel and radial basis function (RBF) kernel were investigated and the linear kernel was found to provide a better result.

In the deep CNN model, we use the AlexNet as the pre-trained model. Figure 3 shows the structure of the AlexNet. As the size of the database is not big, we cannot use a deep model from scratch. Therefore, we select the AlexNet, which is proved to be successful in many applications including the pathology detection [5]. The softmax layer is replaced by a softmax layer of two neurons. The weights of the softmax layer is randomly initialized as before. Once this is done, we fine tune the model using the train subset. The optimization of the weight is done by using a mini-batch stochastic decent algorithm with adaptive learning rate. The learning rate of the later layers is set higher than the learning rate of the initial layers.

We also proposed a fusion-based CNN model for EEG pathology detection. In this model, the AlexNet is used as a basic model. The whole length of the EEG signal is equally divided into three segments. Each segment is preprocessed

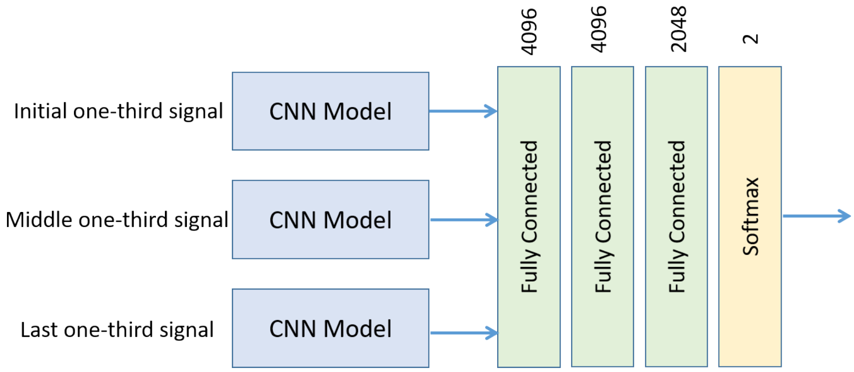

FIGURE 4. Architecture of fusion network.

and fed into the CNN model as before. Features from the last fully-connected layer of the CNN model are used for fusion. Such features from the three segments are fused using an MLP having three fully-connected layers. Finally, a softmax layer is used as the output layer. Figure 4 shows the architecture of the fusion model. Different numbers of neurons were investigated in the experiments; the best result was obtained with 4096 neurons each in the first and the second fully-connected layers and 2048 in the third fully-connected layer. Initial random weights are optimized using the stochastic gradient decent algorithm.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

We performed several experiments for EEG pathology detection using the TUH EEG Abnormal Corpus v2.0.0. Here we present important results found in the experiments.

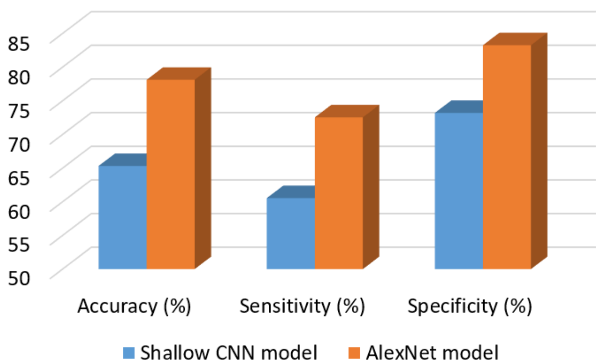

FIGURE 5. Comparison of performances between the shallow CNN model and the AlexNet model.

Figure 5 shows the accuracy, the sensitivity, and the specificity of the proposed system with the shallow CNN model and the AlexNet model. The experiments were performed when each of the files in the train subset and the evaluation subset is four minutes long. From Figure 5, we can see that the AlexNet model outperforms the shallow model in terms of accuracy, sensitivity, and specificity. For example, the accuracy using the AlexNet was 78.12% and that using the shallow model was 65.12%. As the number of the samples in the database is not huge, a model from the scratch such as the shallow model did not perform well. In the subsequent experiments, we restrict ourselves to the AlexNet model only.

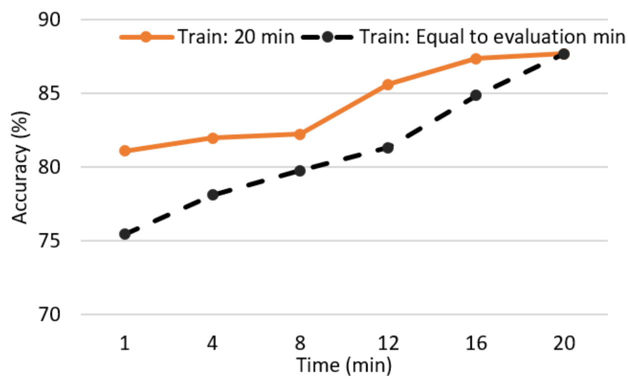

FIGURE 6. Comparison of accuracies obtained using different lengths of signals.

In the next set of experiments, we tried to understand the effect of the length of EEG signals in the train and the evaluation datasets. Figure 6 shows the accuracies of the system while varying the length of the signals. In one experiment, the length of the signals in the train subset was fixed to 20 minutes. The length of the signals in the evaluation subset varied between one minute to 20 minutes. While the length was one minute, the accuracy was 75.46%, and while the length was 16 minutes, the accuracy was 84.86%. In another experiment, the lengths of signals in both the train and the evaluation subsets remained the same. For example, if the length of signals in the train subset was four minutes, the length of signals in the evaluation subset was also four minutes. From Figure 6, we see that latter experiment provided better accuracies than the first experiment. For one minute signals, the accuracy was 81.1% and for 16 minutes' signals, the accuracy was 87.37%.

Figure 7 shows various performance measures in terms of a confusion matrix obtained by the proposed system without the fusion. The length of the signals was 20 minutes.

Targets

Predictions	Normal	Abnormal	
Normal	99	7	Precision = 93.40
Abnormal	27	143	
	Sensitivity = 78.57	Specificity = 95.33	Accuracy = 87.68

FIGURE 7. Confusion matrix of the system without fusion.

The accuracy was 87.68%. This was the best accuracy by the system without the fusion.

Targets

Predictions	Normal	Abnormal	
Normal	101	5	Precision = 95.28
Abnormal	25	145	
	Sensitivity = 80.16	Specificity = 96.67	Accuracy = 89.13

FIGURE 8. Confusion matrix of the system with fusion.

Figure 8 shows the confusion matrix of the system using the fusion. The accuracy was 89.13%. All the performance measures were better than those without the fusion. This clearly states the significance of fusing features from different temporal segments of the EEG signal.

TABLE 2. Comparison of accuracies between the systems.

Systems	Accuracy (%)
[29]	78.8
[30]	85.4
[5]	87.32
Proposed system without fusion	87.68
Proposed system with fusion	89.13

Table 2 gives a comparison of accuracies between the systems using the same database. From the table, we find that the proposed system outperformed all other system. The system with the fusion performed the best.

V. CONCLUSION

An EEG pathology detection system using the CNN model was proposed. The EEG signals were preprocessed and their spatio-temporal representations were fed to the CNN model. One shallow CNN model and one deep CNN model in the form of the AlexNet were investigated. The fusion of CNN features of three distinct temporal segments of the EEG signal was realized using the MLP. Experiments were performed on a publicly available database. Experimental results showed that the proposed system with the fusion achieved the highest accuracy, and outperformed other related systems.

In a future study, we will investigate different fusion strategies in the proposed system.

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